Development of Micro Wireless Sensor Platforms for Collecting Data of Passenger-Freight Interactions

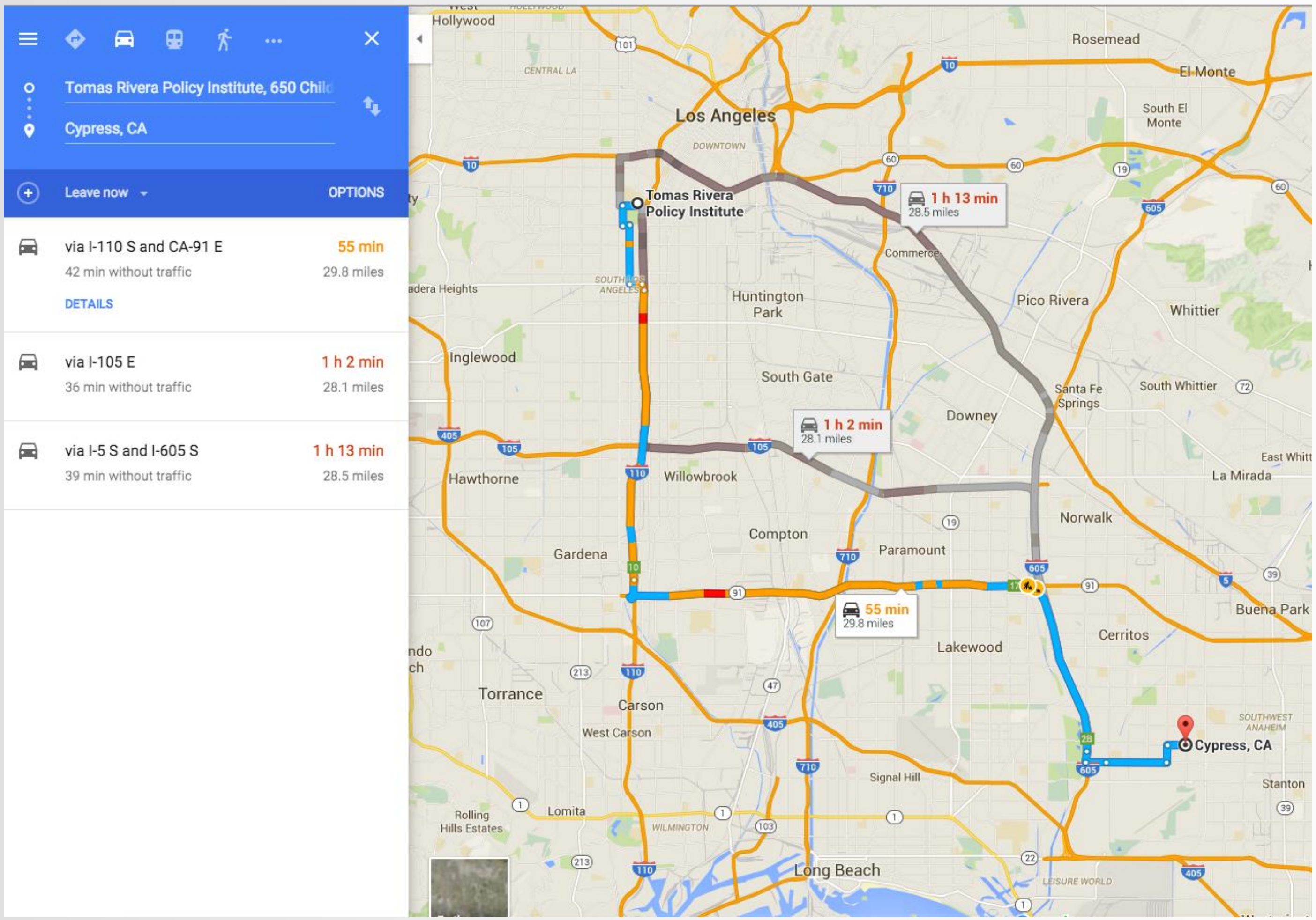
Mohammad Mozumdar

<u>Graduate Students:</u> Kyle Ying, Alireza Ameri, Ankit Trivedi, Dilip Ravindra, Darshan Patel, Varun Sharma, Ashutosh Parhad

Department of Electrical Engineering
California State University Long Beach

The thing we don't like but have to face everyday – Road Traffic!

But we can make smarter turn with real time traffic!



Google Maps showing optimized route from USC to Orange County

How exactly does Google Maps/Garmin/TomTom know how clogged the highway is on your way out to home or office?

The traffic information comes from a variety of sources:

- Commercial traffic data providers (INRIX, Tele Atlas, HERE, ..)
- Departments of Transportation
- State agency – Caltrans

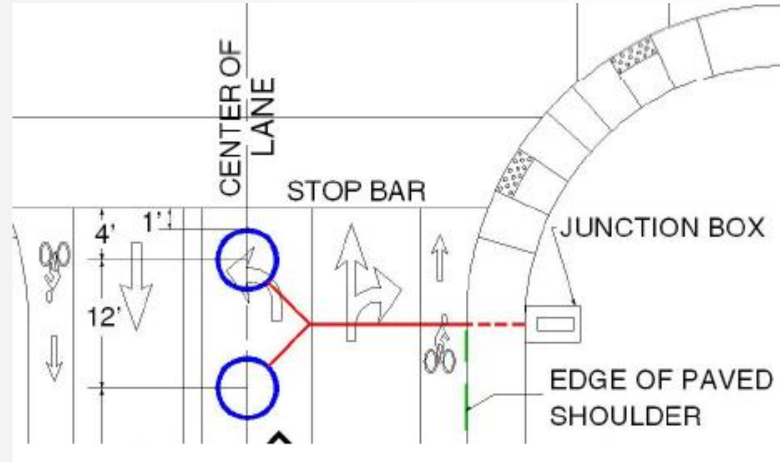
Raw data is collected from:

- Mobile users (Google Maps)
- **<u>Road sensors</u>**
- Traffic cameras, and even through aircraft

This information is compiled and delivered via radio frequency (FM/HD Radio™ or satellite) to your navigation system.

Road Sensors: Inductive Loop

Physical Representation

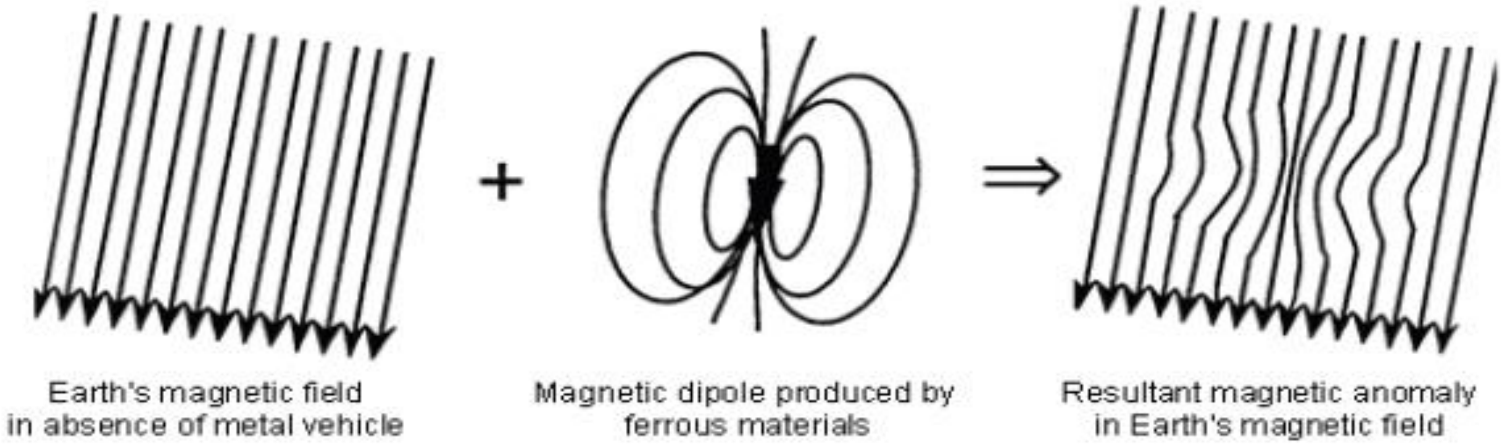


Source: US DoT Federal Highway Administration

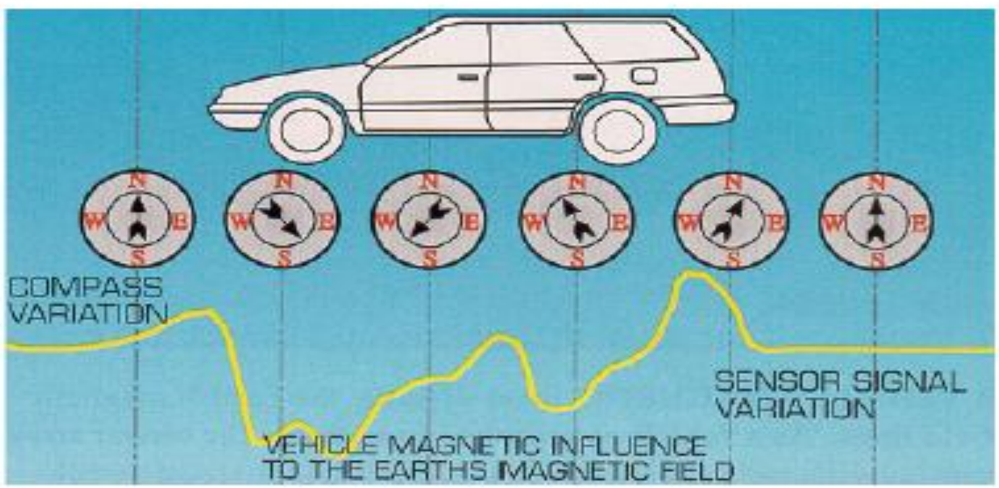
Loop Detector Schematic

- Existing traffic/vehicle detection is determined with "Inductive Loop" technologies
- These loops generate a magnetic field that operates at frequencies typically less than 1kHz
- Large rectangular loops (4' x 8', 6' x 8', 6'x 12' are used to detect larger vehicles
- Small size loops (i.e. 2' x 5', 3' x 6', 6' x6') are used to detect smaller vehicles, such as motorcycles and automobiles

Road Sensors: Inductive Loop



(a) Magnetic anomaly induced in the Earth's magnetic field by a magnetic dipole.



(b) Perturbation of Earth's magnetic field by a ferrous metal vehicle

Source: US DoT Federal Highway Administration

Inductive Loop Pros & Cons

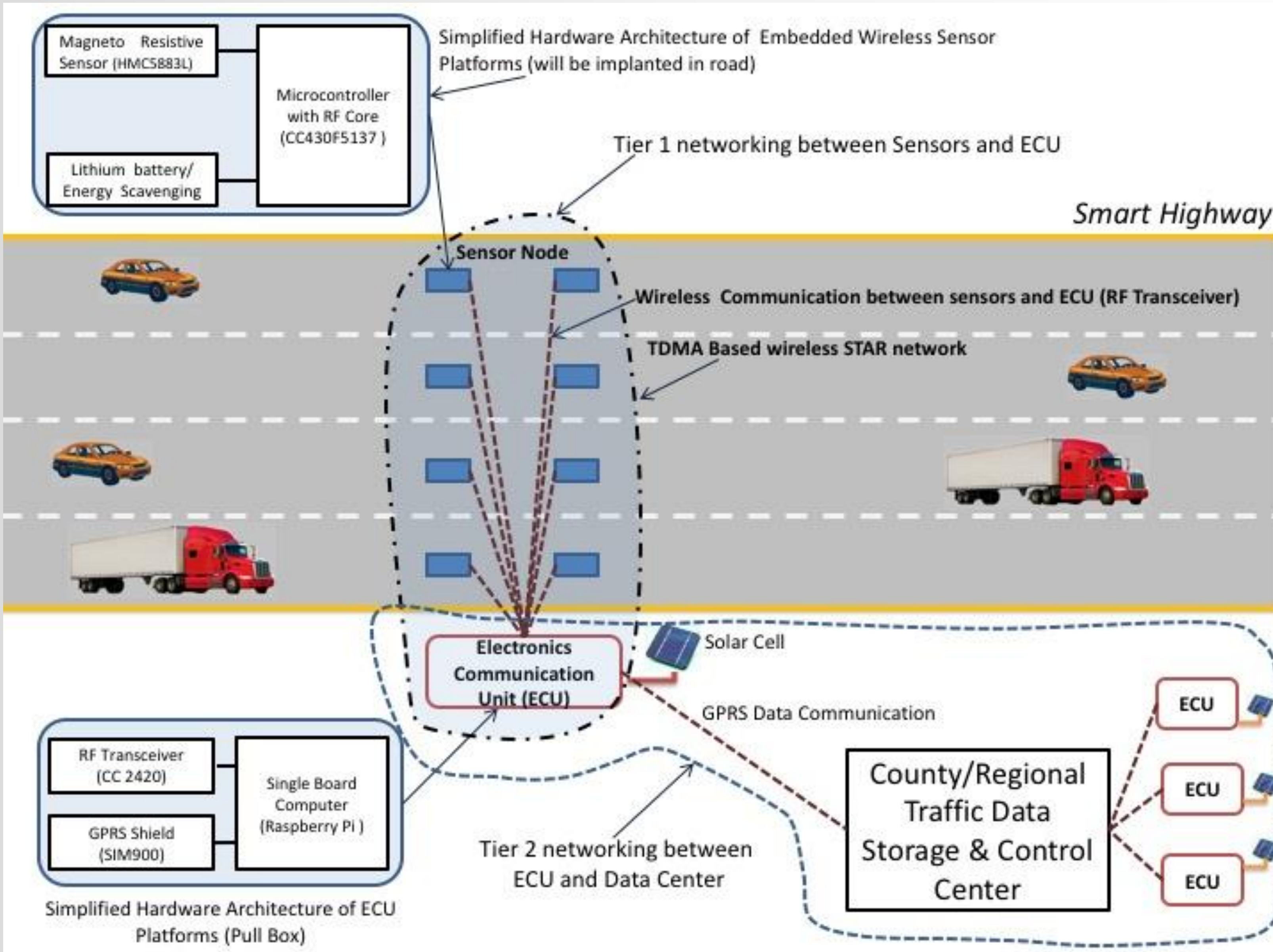
Advantages

- Detects ferrous objects precisely
- Typically immune from environmental effects such as weather, temperature, a terrain variations

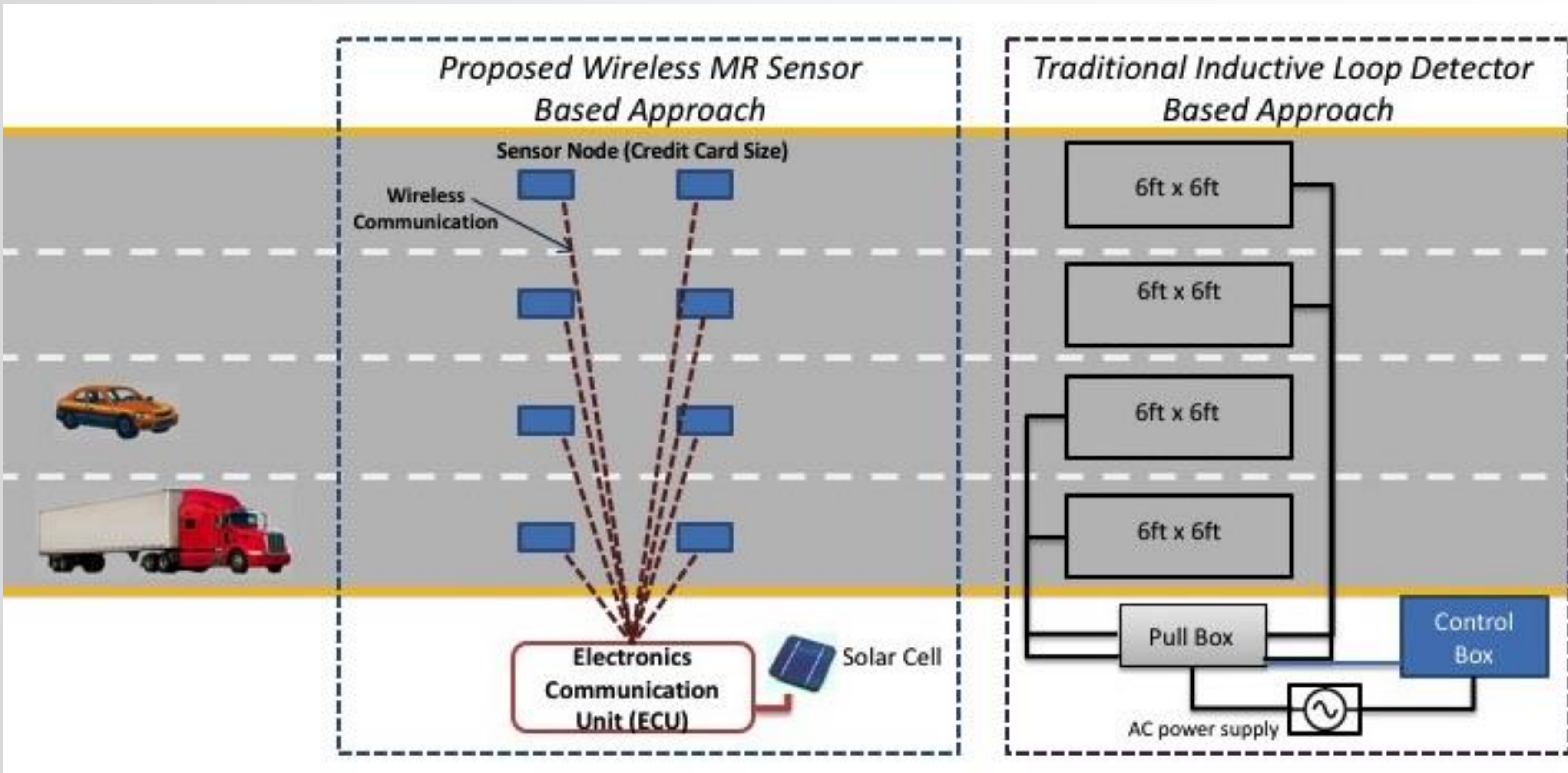
Disadvantages

- Expensive to install and maintain ($$$)
- Relatively significant power usage for the generation of the magnetic field.
- Large area usage (greater than 10 sq.ft.)

Proposed Solution For Smart Road



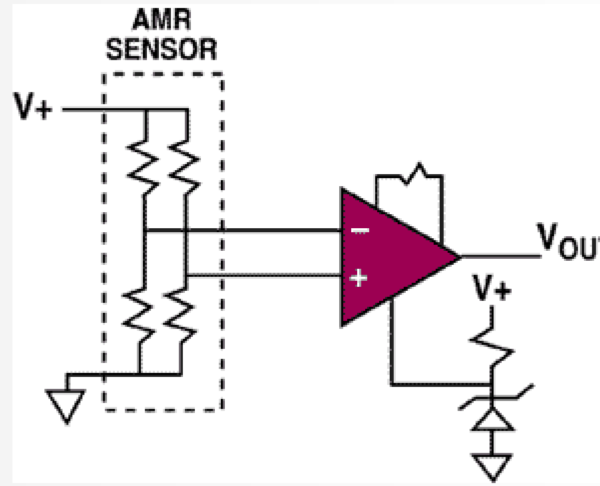
Proposed VS Traditional Inductive Loop Based System

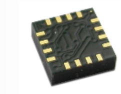


Anisotropic Mangeto-Resistive Sensors (AMR) IC Sensor

AMR Sensor IC (Honeywell HMC5883L 3-axis magnetometer- 3mm in size **)**

- Wheatstone bridge variable resistor network that changes resistance w.r.t. changes to the magnetic field
- Provides the same advantages to inductive loop technologies without the power and area disadvantages
- Power consumption extremely low (~200uA at lower sampling rates)

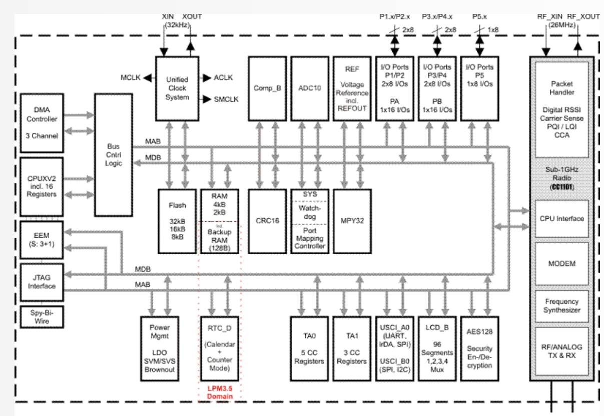




Source: Honeywell

Microcontroller (CC430F5137 **)**

- Low power modes (LPM) for sleep between computational and communication operations
- Single package μproc and RF core for low area wireless transmissions



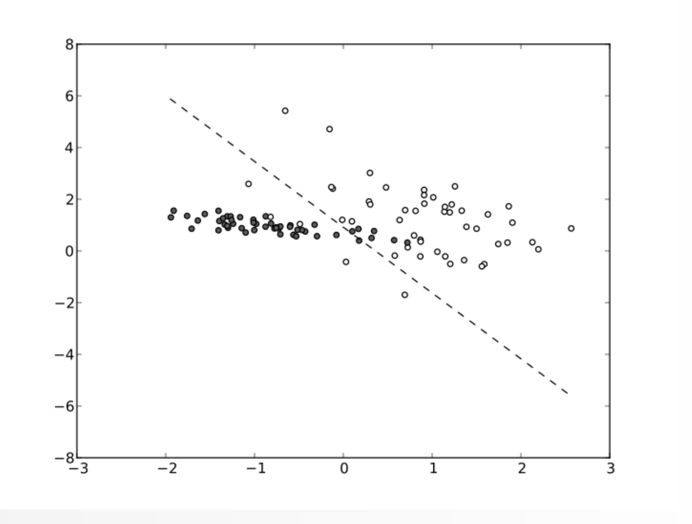
Source: Texas Instruments

Machine Learning Based Vehicle Classification

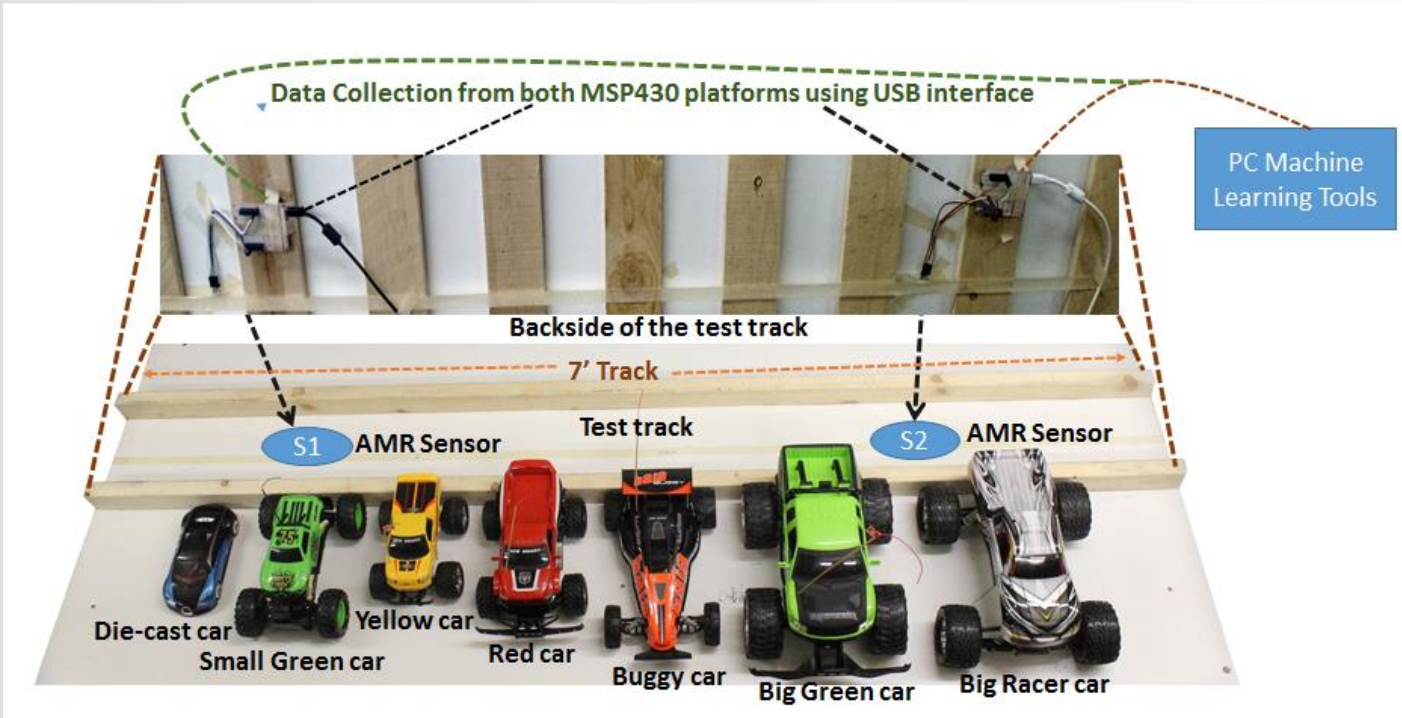
- Useful when the sets of data is large enough that human observations for extracting patterns in data become impractical.
- Typically associated with the field of data mining
- Pattern recognition based on a set of rules

General Idea:

- Collect vehicle data crossing the AMR sensor
- Utilize ML tools to generate a model for classification



Our Lab Testbed Setup



- 7 different RC Vehicles with a variety of similar and different attributes
- 7 ft straight track for each vehicle to make passes
- 2 sensors roughly 4' apart to take gather readings and classify

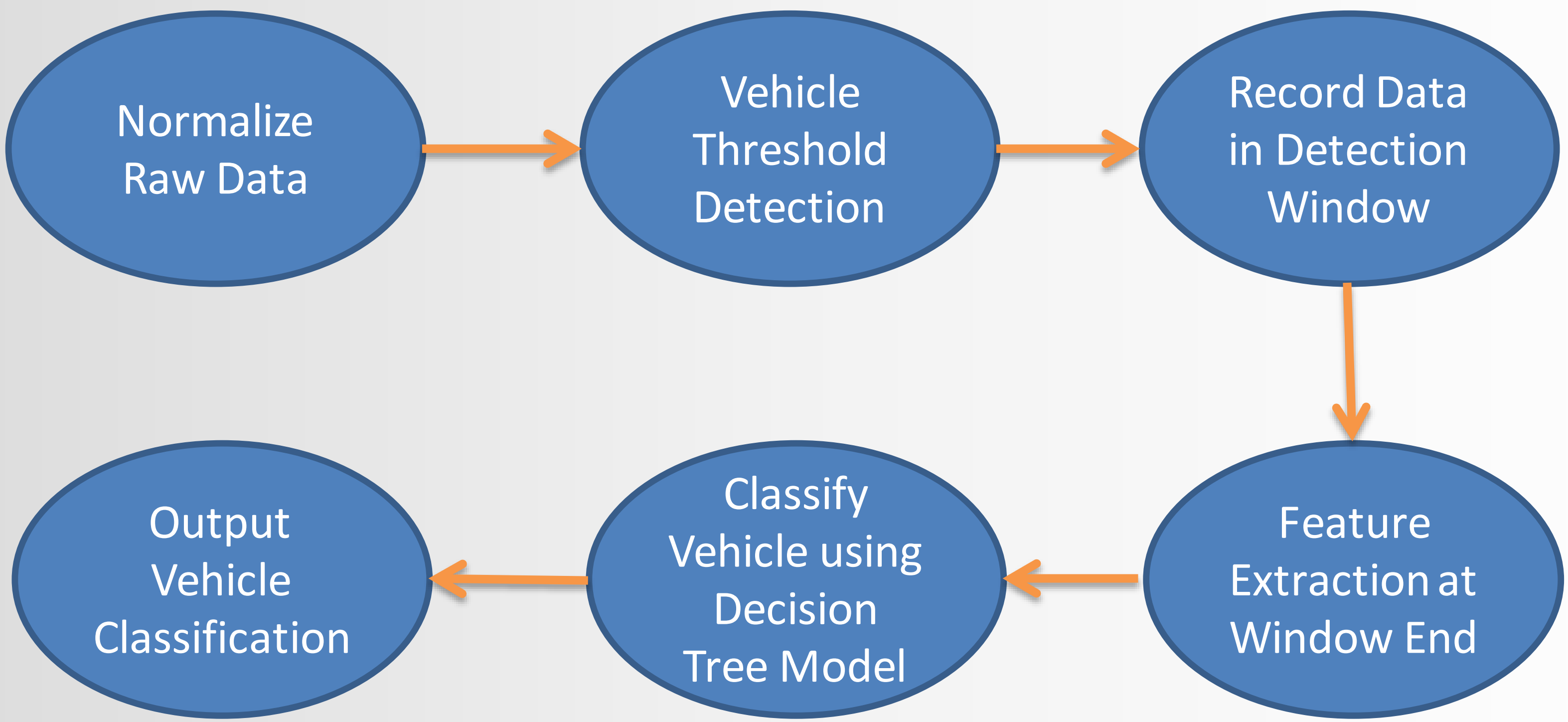
Data Collection for supervised machine learning

- We collected data for each of the 7 vehicles across 350 runs over 2 sensors
- Total : 700 samples, 100/class for training

Why a decision-tree based algorithm?

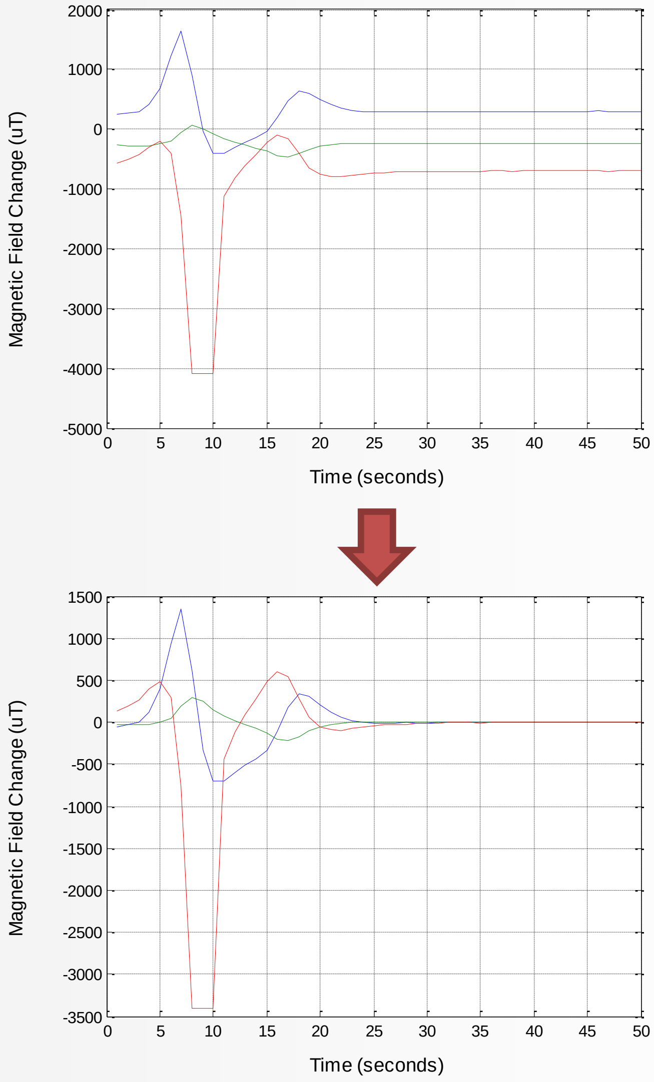
- Simple and computationally efficient tree
- Simplicity of implementation in software

Implementation Flowchart



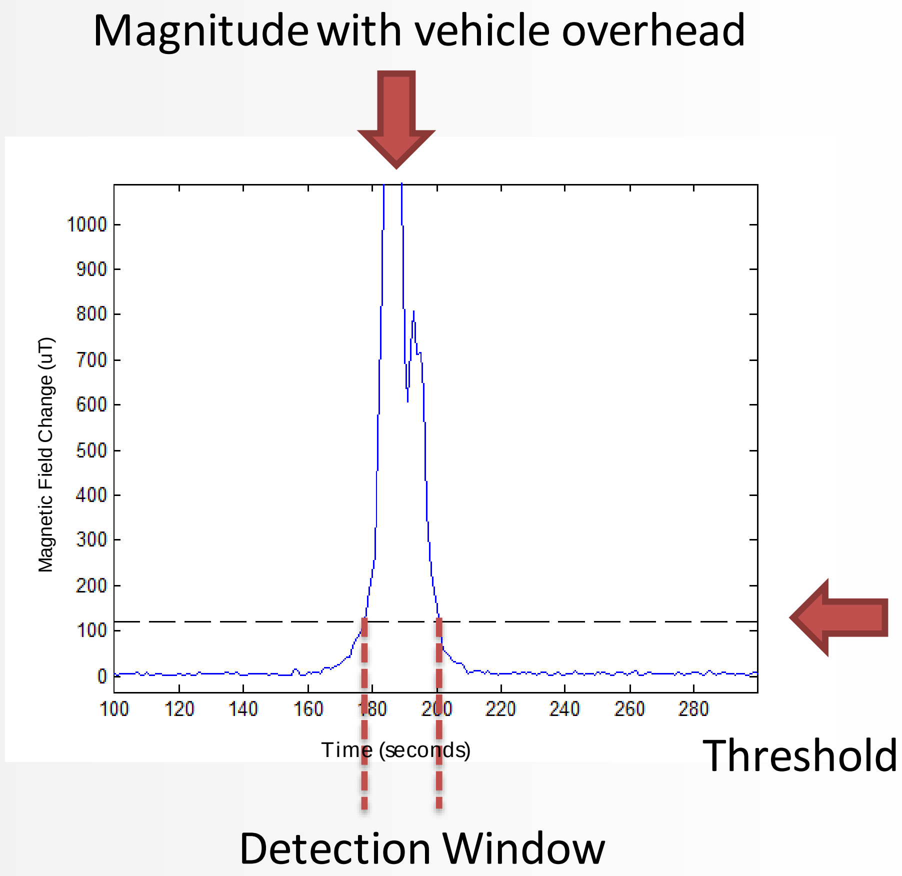
Adaptive Baseline

- Zeroing the background environmental magnetic field by offset
- Allows for the reuse of the same vehicle detection and classification algorithm in multiple environments
- Noise removal can be implemented at this stage



Threshold Detection

- Once a vehicle passes the threshold the detection flag triggers and a certain number of samples are recorded for processing



Features Collected from Vehicles

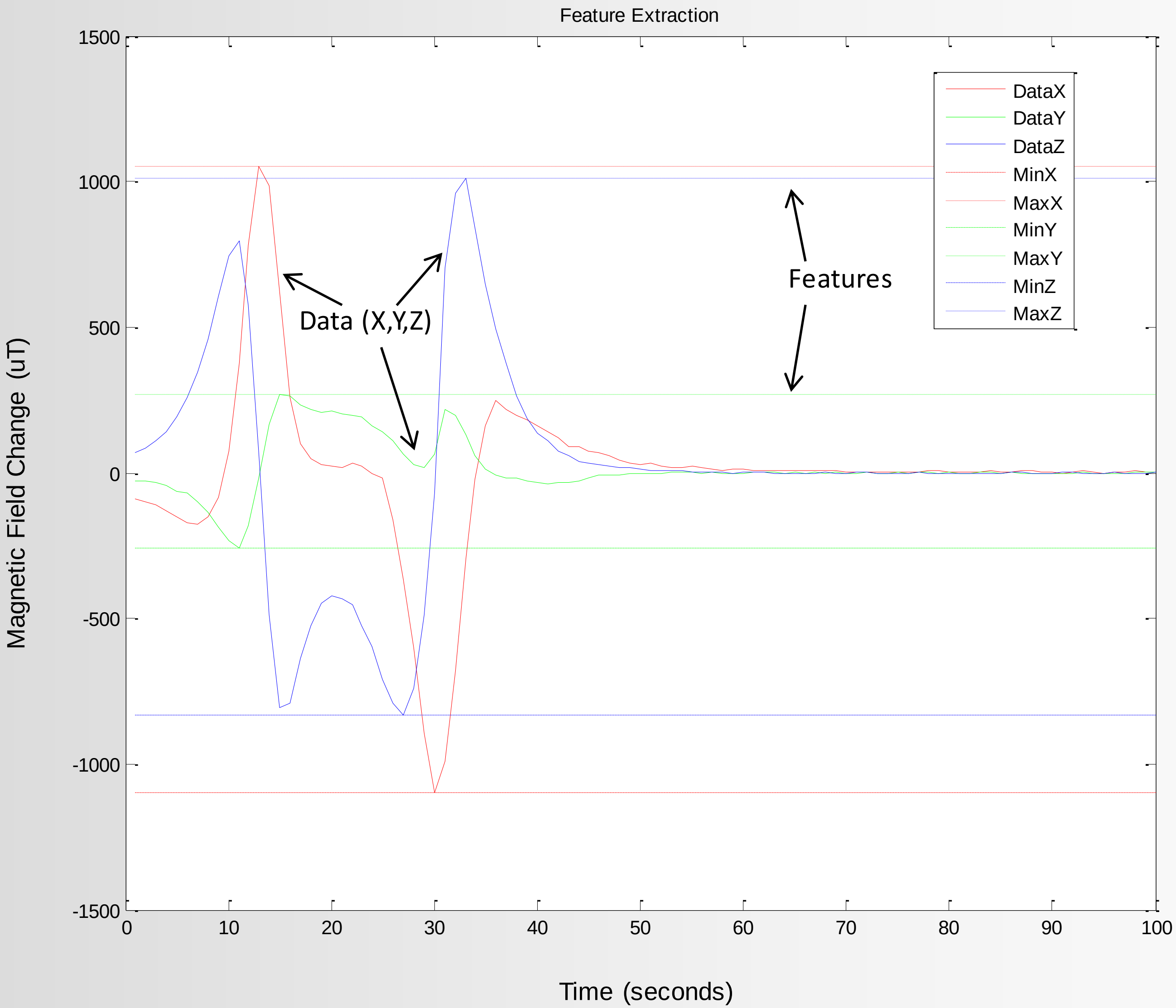
Interesting Features:

- **Min:** minimum value of an axis during the detection window
- **Max:** maximum value of an axis in the window
- **Mean:** average of all axis values in the window
- **Range:** Maximum – Minimum

Using a 3-axis sensor this results in 12 unique features

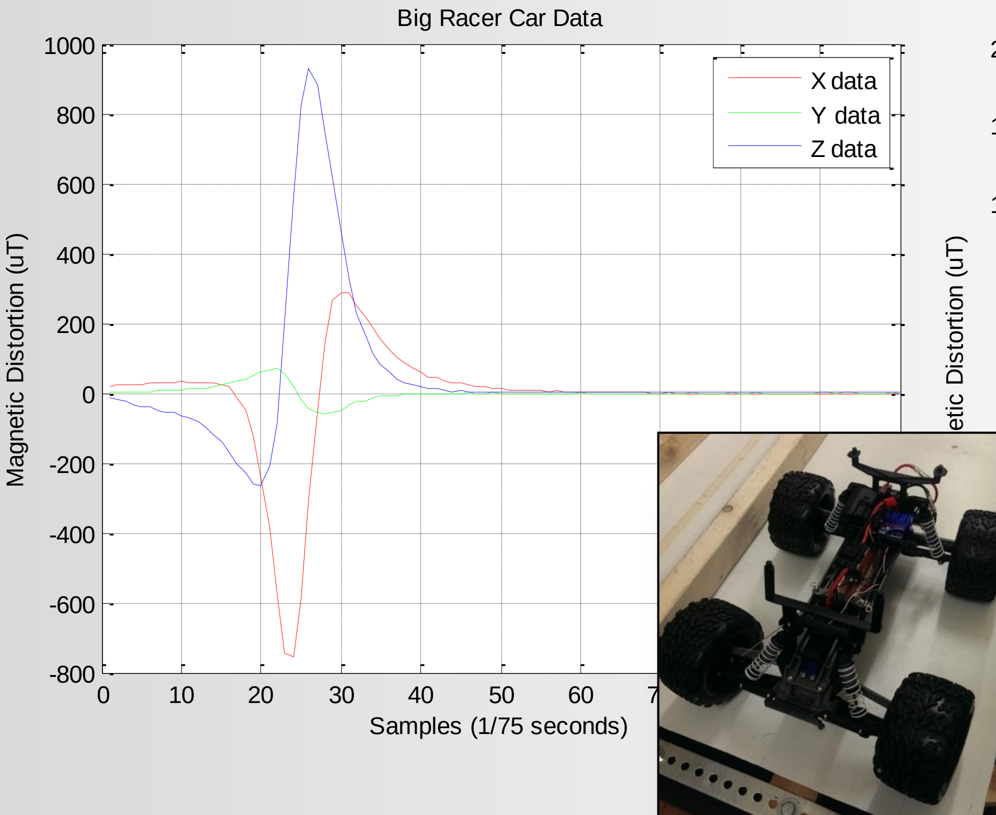
These Features are very simple to calculate and compute

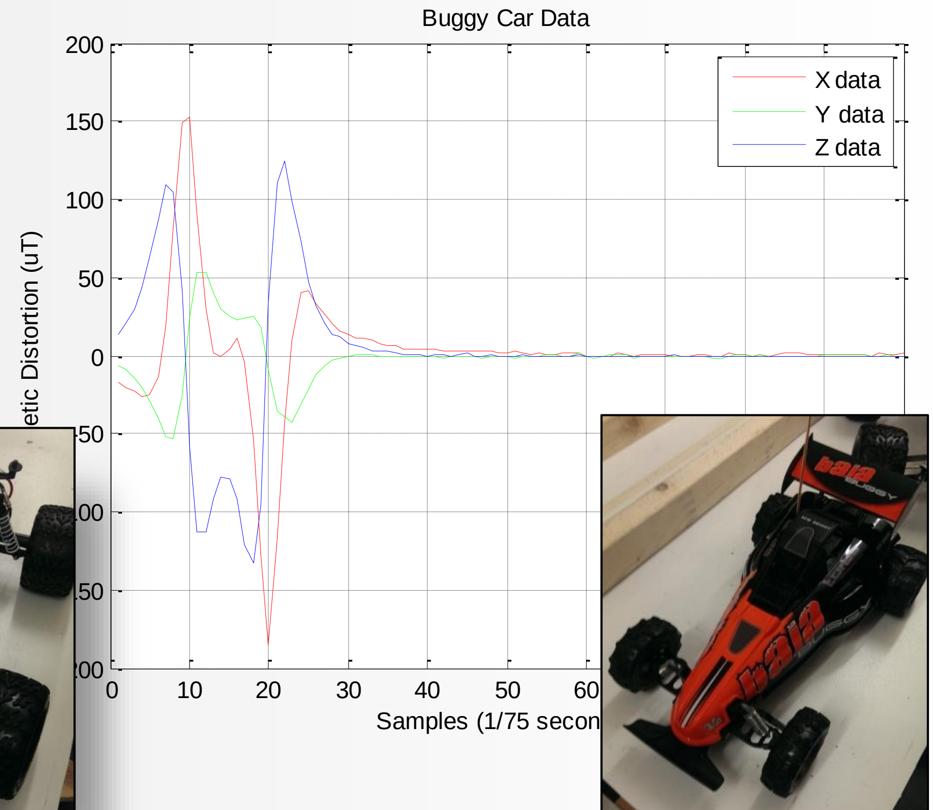
Example Plot and Feature Extraction



MinX=-1097
MinY=-256
MinZ=-834
MaxX=1054
MaxY=267
MaxZ=1011
MeanX=4.01
MeanY=17.13
MeanZ=7.48
RangeX=2151
RangeY=523
RangeZ=1845

Example Car Data





Similar Sizes but Different Signatures!

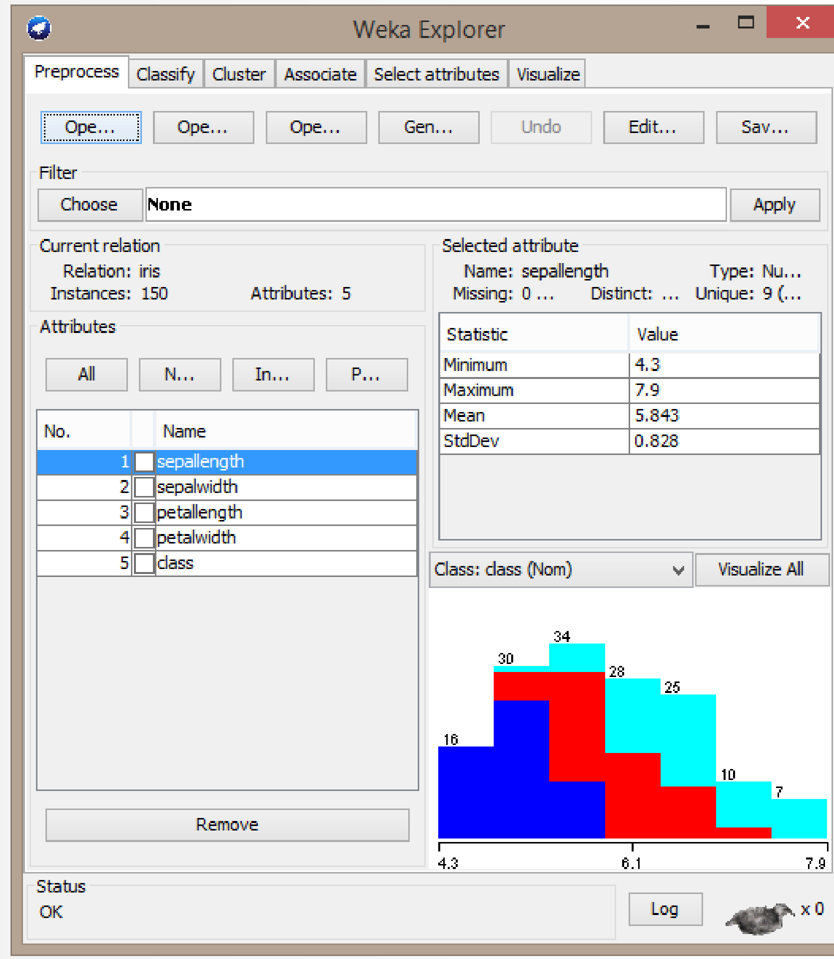
Machine Learning: decision tree learning (J48)

J48 is the open source Java implementation of C4.5/ID3 developed by John Quinlan

Inputs: multiple features corresponding to a single classifier

Note: higher # samples per classifier results in a more accurate output tree

Output: a decision tree with the highest classification rate given the features



Source: University of Waikato, WEKA

WEKA output

```
J48 pruned tree
------------------
```

4 Features Selected

```
range_z <= 2187
|   max_x <= 419.4: 1 (100.0)
|   max_x > 419.4
|   |   max_x <= 791.6
|   |   |   max_x <= 757.8: 5 (94.0)
|   |   |   max_x > 757.8
|   |   |   |   min_y <= -118.2: 2 (4.0)
|   |   |   |   min_y > -118.2: 5 (6.0)
|   |   max_x > 791.6: 2 (96.0)
range_z > 2187
|   min_y <= -1103.8
|   |   range_z <= 3725: 6 (60.0)
|   |   range_z > 3725
|   |   |   mean_z <= -168.58: 4 (101.0/1.0)
|   |   |   mean_z > -168.58: 6 (36.0)
|   min_y > -1103.8
|   |   mean_z <= -116.47
|   |   |   range_z <= 3796: 6 (3.0)
|   |   |   range_z > 3796: 7 (100.0)
|   |   mean_z > -116.47: 3 (100.0)

Number of Leaves  :     11

Size of the tree :      21


Time taken to build model: 0.03 seconds
```

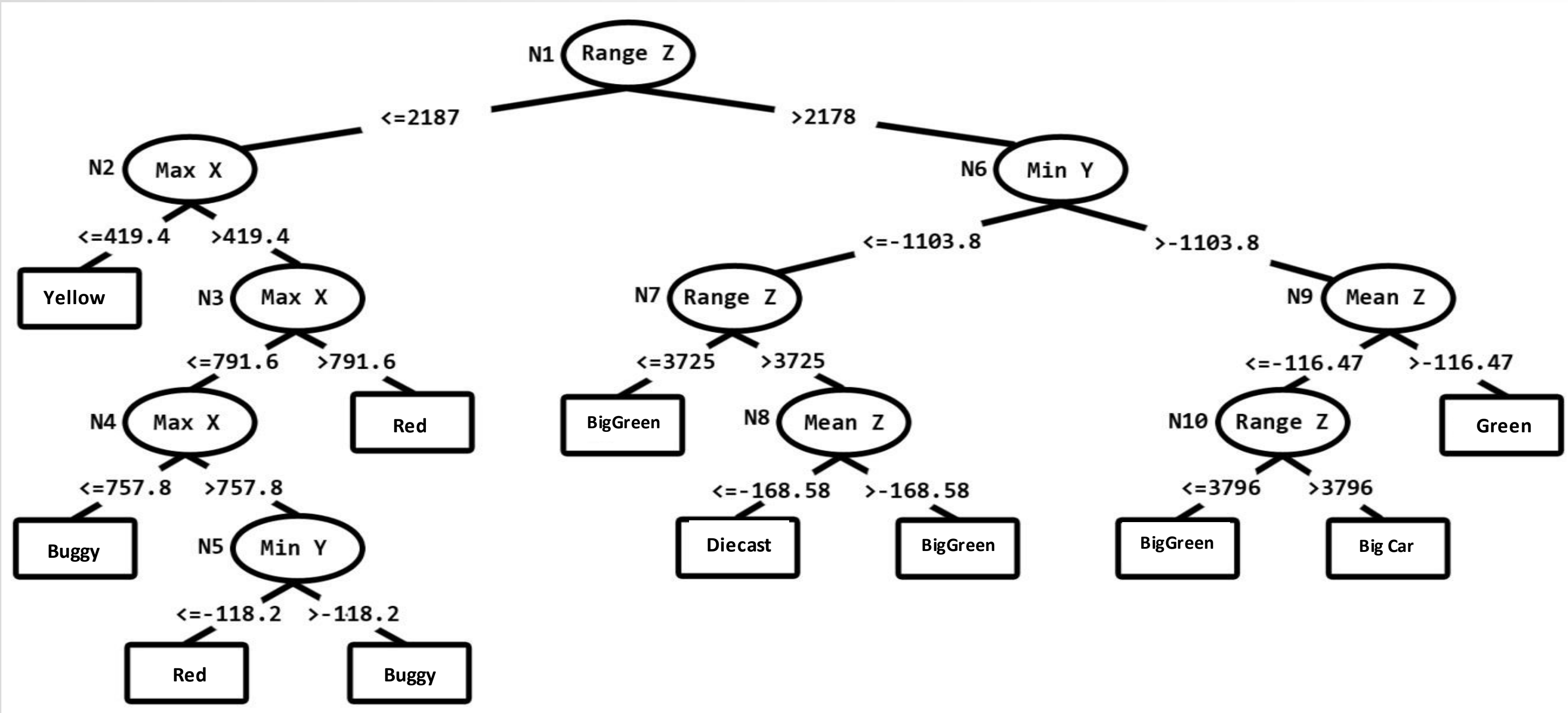
Fast!

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         692               98.8571 %
Incorrectly Classified Instances         8                1.1429 %
Kappa statistic                          0.9867
Mean absolute error                      0.0037
Root mean squared error                  0.0572
Relative absolute error                  1.4927 %
Root relative squared error             16.3407 %
Total Number of Instances              700
```

Accuracy Rate

```
=== Confusion Matrix ===

   a   b   c   d   e   f   g   <-- classified as
 100   0   0   0   0   0   0 |   a = 1
   0  99   0   0   1   0   0 |   b = 2
   0   0 100   0   0   0   0 |   c = 3
   0   0   0  97   0   3   0 |   d = 4
   0   1   1   0  98   0   0 |   e = 5
   0   0   0   1   0  99   0 |   f = 6
   0   0   1   0   0   0  99 |   g = 7
```

Graphical Tree



Node Num.	Information Gain Attribute				Best Attribute
	Min Y	Max X	Mean Z	Range Z	
1	0.9527	0.8002	0.9031	0.9868	Range Z
2	0.3339	0.9707	0.3978	0.3846	Max X
3	0.3060	0.8411	0.2155	0.3068	Max X
4	0	0.1735	0	0.0379	Max X
5	0.7108	0	0.7108	0.0570	Min Y
6	0.9317	0.1864	0.7574	0.4976	Min Y
7	0.2047	0.1601	0.3717	0.4249	Range Z
8	0.1386	0.4467	0.8798	0.0084	Mean Z
9	0.5724	0.3189	0.9625	0.8676	Mean Z
10	0	0	0.0066	0.6627	Range Z

Brute Force Search for Best Results

- The output tree doesn't always generate the best results given a large number of features
- Due to fast processing time to generate the output tree, we can easily calculate all combinations (n choose k)

$$\binom{n}{k} \text{ or } {}_{n}C_{k}$$

- We use *n=2,3,4* where *k=12*

Feature Performance

2 features (66 combinations):

Comb#	Classification%	Features
64	94%	minx maxx
58	93%	minx rangex
30	93%	maxx rangey
60	91%	minx meany

3 features (220 combinations):

Comb#	Classification%	Features
219	98%	minx miny maxx
200	98%	minx maxx maxz
194	97.8571%	minx maxx rangez
57	97.8571%	maxx rangey rangez
149	97.7143%	miny maxx rangez

4 features (495 combinations):

Comb#	Classification%	Features
479	98.8571%	minx miny maxx rangez
270	98.8571%	miny maxx meanz rangez
390	98.7143%	minx maxx meanz rangez
78	98.7143%	maxx meany meanz rangez

.

Best Results Simulated vs. Testbed

Simulated Results

Cross-Validation Percentages	
Number of Features (Attributes)	Accuracy
Three Features (maxx, rangey, rangez)	97.86%
Three Features (miny, maxx, rangez)	97.71%
Four Features (minx, miny, maxx, rangez)	98.86%
Four Features (miny, maxx, meanz, rangez)	98.86%

Actual Results:

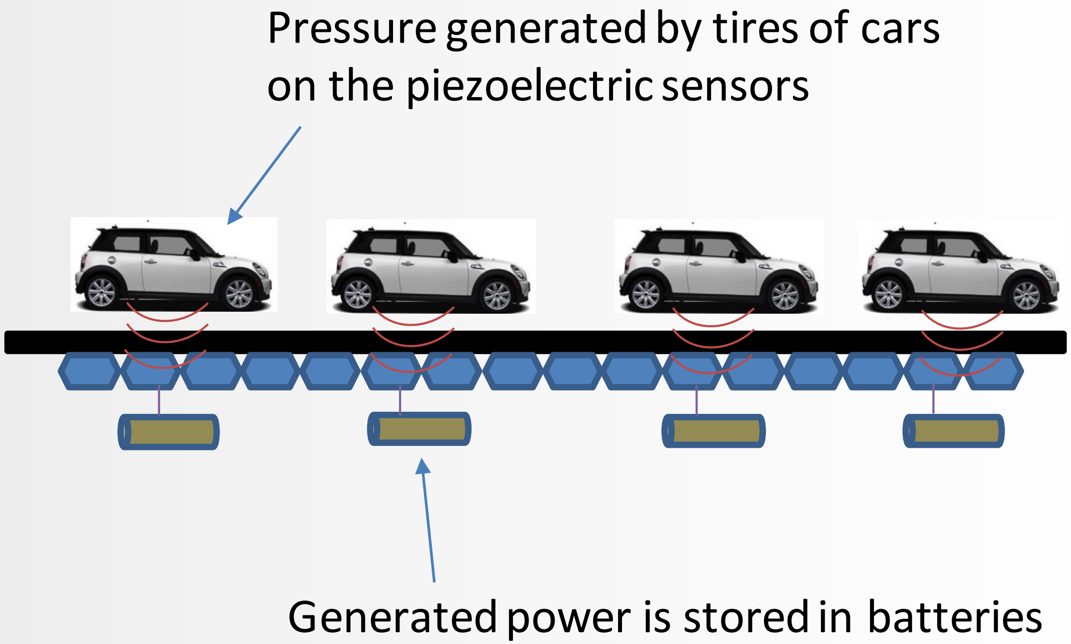
Real world Classification Percentages	
Number of Features (Attributes)	Real-world
Three Features (maxx, rangey, rangez)	98.57%
Three Features (miny, maxx, rangez)	97.38%
Four Features (minx, miny, maxx, rangez)	90.24%
Four Features (miny, maxx, meanz, rangez)	99.05%

Simulated results match real world testing values very closely.

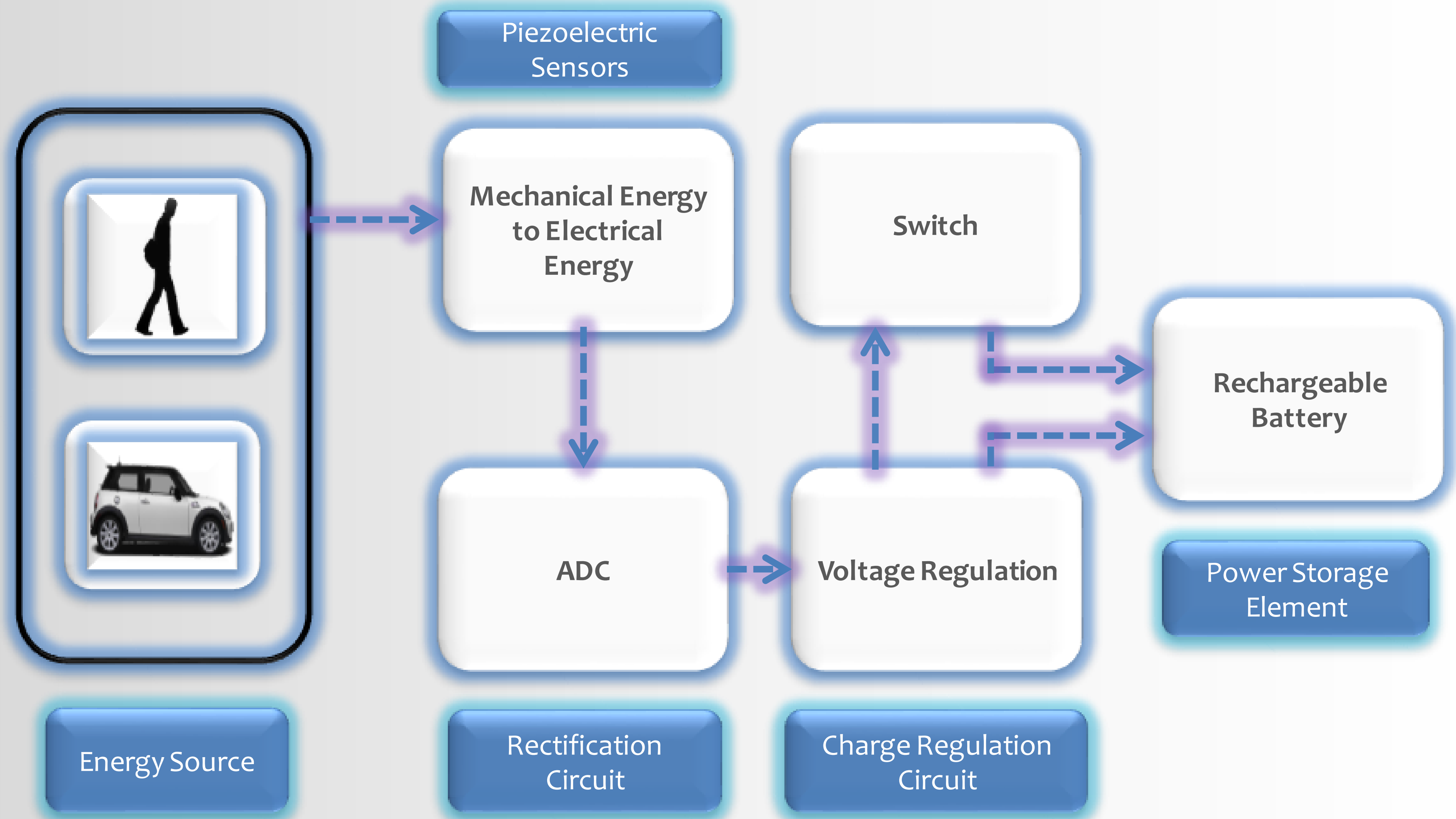
Note: minx results are lower due to clipping

Energy Scavenging Using Piezoelectric Sensors

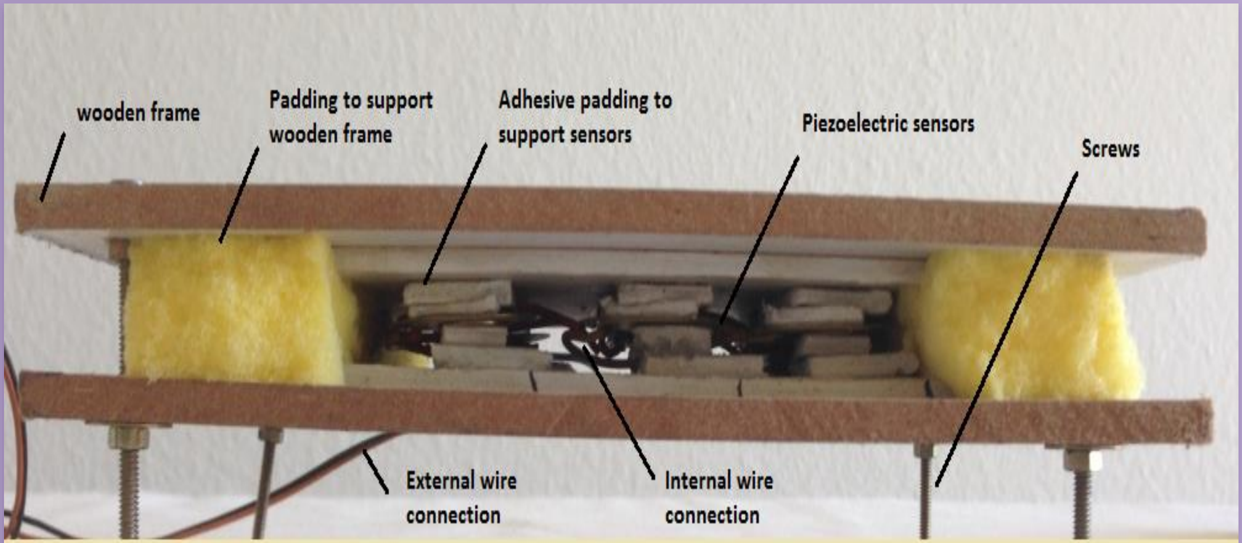
- Mechanical to Electrical energy conversion
- Proper implementation can help in continuous operation of wireless sensors
- Almost 70% of the overall efficiency of the energy scavenging system depends on Piezoelectric sensors
- Applications include consumer electronics, automotive, health, WSN, etc.



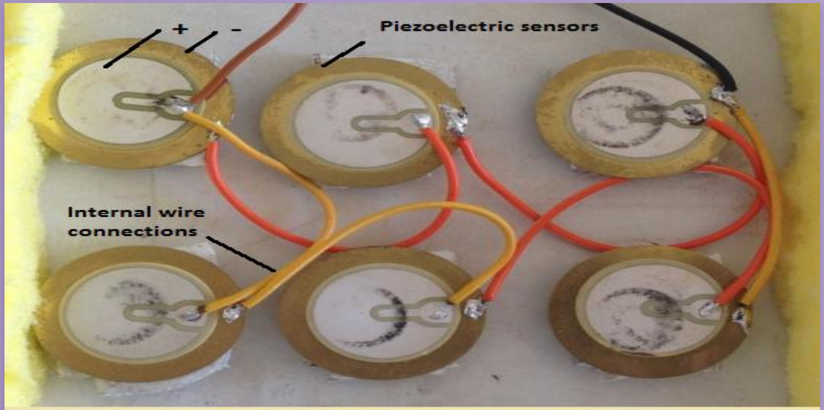
Energy Scavenging System



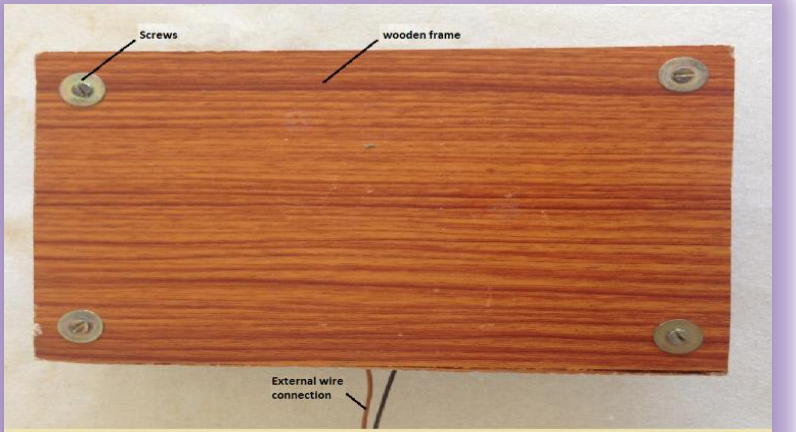
Lab Prototype of Energy Scavenging System



Side View of hardware - arrangement of piezoelectric sensors

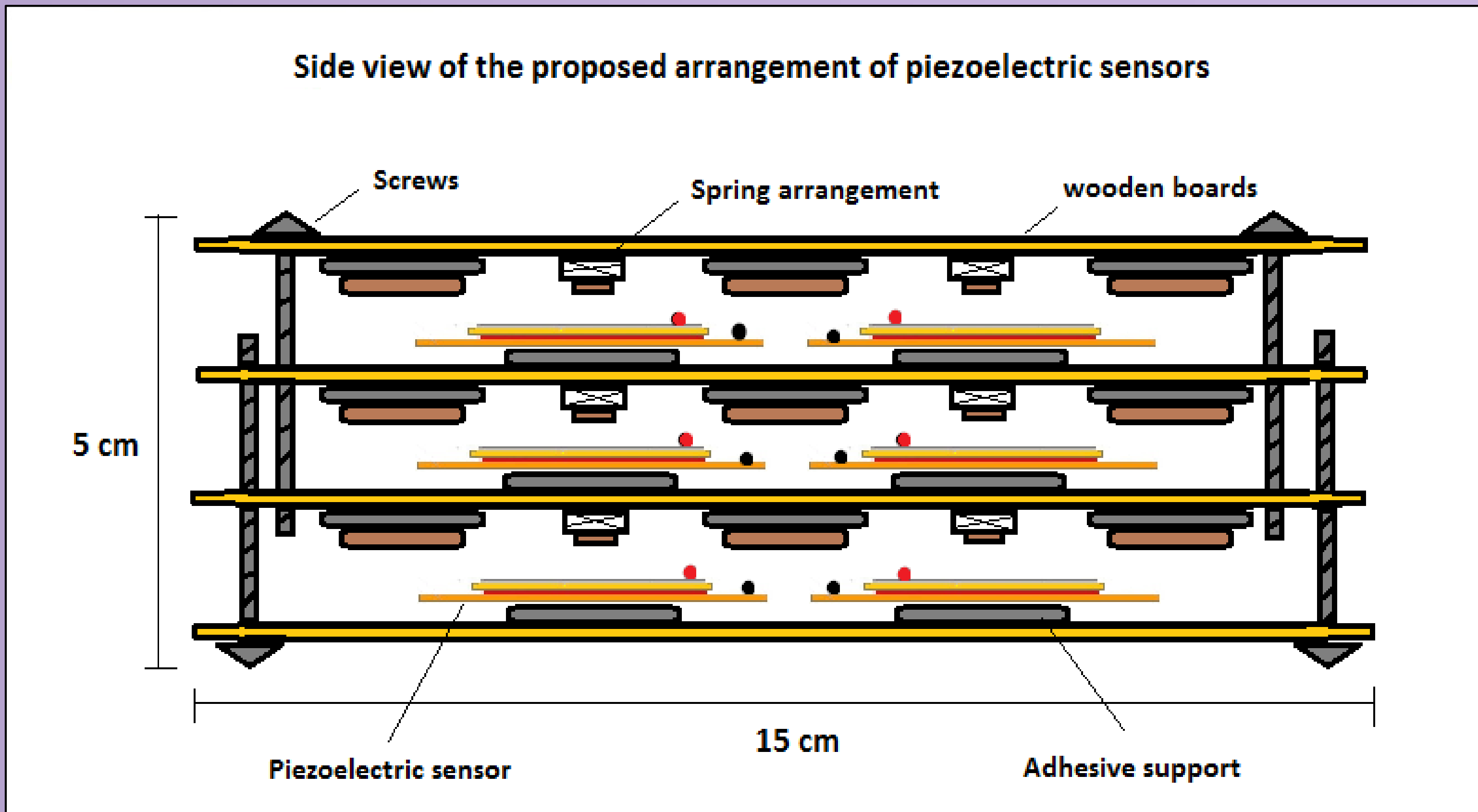


Hardware - Internal wire connections



Top view of hardware - arrangement of piezoelectric sensors

Advanced Energy Scavenging System

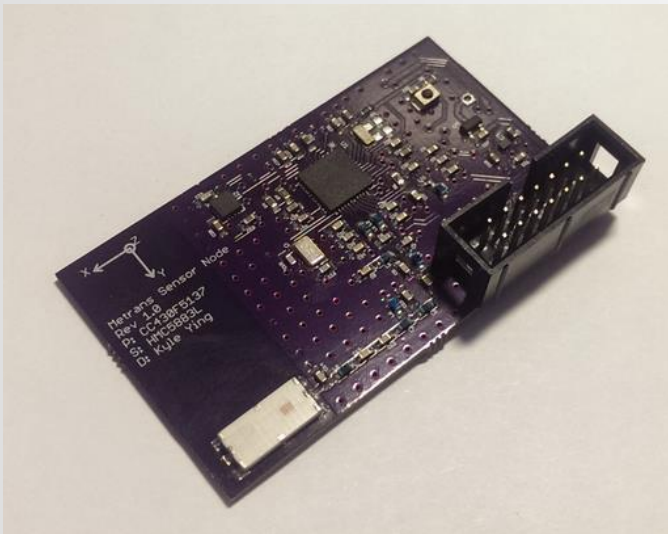


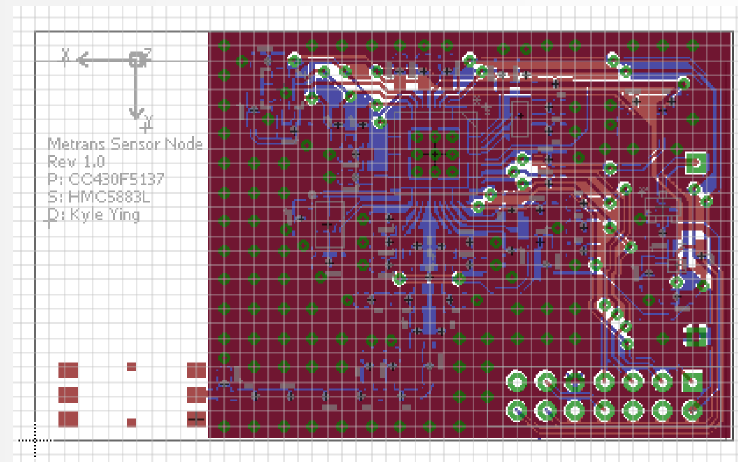
- 3 layers instead of 1 layer/ Smaller size and less implementation cost
- Increase probability of the sensors being pressed in every tap
- Increase number of sensors being pressed in a single tap

Energy Scavenging System

- 1 AA rechargeable battery can be charged in 10 -12 hours with vehicles and pedestrians passing over the sensors in every 5 seconds using the designed hardware
- The sensors placed on crosswalks can increase the average number of taps
- Charging rate would be better if the efficiency and the number of sensors used are increased

Designed Smart Traffic Sensing Node





- Size: 2 ½” x 1 ½” x ¾” (with AA battery pack)
- Dimensions will change depending on the battery pack used in future implementations

Final Remarks

The system described in this presentation can replace current inductive loop technologies with:

- Maintain traffic/vehicle detection capabilities
- Additional features such as vehicle classification
- Lower power consumption
- Lower physical area utilization

In addition, many classifiers can be used at high accuracy rates compared to other methods utilizing solely novel features.

Related Publications

- K. Ying, A. Ameri, A. Trivedi, D. Ravindra, D. Patel, M. Mozumdar,” Decision Tree-based Machine Learning Algorithm for In-node Vehicle Classification”, Proceedings of IEEE Green Energy and Systems Conference, Long Beach, November 2015, USA

- V. Sharma, A. Parhad, M. Mozumdar, “Energy Scavenging Using Piezoelectric Sensors to Power in Pavement Intelligence Vehicle Detection Systems”, METRANS International Urban Freight Conference , Long Beach, 2015

Questions?